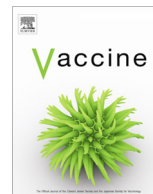




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Optimizing vaccine distribution via mobile clinics: a case study on COVID-19 vaccine distribution to long-term care facilities



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ABSTRACT

Background: People living in clustered communities with health comorbidities are highly vulnerable to COVID-19 infection. Rapid vaccination of vulnerable populations is critical to reducing fatalities and mitigating strain on healthcare systems. We present a case study on COVID-19 vaccine distribution via mobile vans to residents/staff of 47,907 long-term care facilities (LTCFs) across the United States that relied on algorithms to optimize vaccine distribution.

Methods: We developed a modeling framework for vaccine distribution to high-risk populations in a supply-constrained environment. Our framework decomposed this challenge as two separate problems: an assignment problem where we optimally mapped each LTCF to select CVS stores responsible for distributing vaccines; and a scheduling problem where we developed an algorithm to assign available resources efficiently.

Results: We assigned 1,214 retail stores as depots for vaccine distribution to LTCFs throughout the United States. Forty-one percent of matched depot-LTCF pairs were within 5 miles of a depot, 74% were within 20 miles, and only 8% mapped to depots farther than 50 miles away. Our two-step approach ensured that the first LTCF vaccination dose was distributed within 9 days after the program start date in 76% of states, and greater than 90% of doses were administered in the minimum amount of time.

Conclusions: We demonstrate that algorithmic approaches are instrumental in maximizing vaccine distribution efficiency. Our learning and framework may be of use to other organizations, including communities where mobile clinics can be established to efficiently distribute vaccines and other healthcare resources in a variety of scenarios.

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1. Introduction

The novel coronavirus disease-2019 (COVID-19) pandemic caused by severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) erupted in early December of 2019 in Hubei province of the People's Republic of China and has since taken the lives of more than 5.2 million people worldwide [1]. The United States (US) accounts for around 20% of those deaths. Of the total deaths in the US, approximately 34% are due to fatalities in long-term care facilities (LTCFs), although fewer than 1% of the country's population lives in this form of housing [2]. This discrepancy highlights the disproportionate impact of the pandemic on individuals who live in LTCFs, as well as the extreme vulnerability of high-risk individuals living in clustered communities where social distancing is difficult. Vulnerability to COVID-19 is further enhanced by the fact

that long-term care (LTC) residents are primarily older adults, with a majority aged 65 and over, whose capacity for self-care may be limited because of chronic illness, injury, or physical or cognitive impairment [3]. In recognition of the significant risk factors affecting this community, the Centers for Disease Control and Prevention (CDC) Advisory Committee on Immunization Practices identified individuals at LTCFs, including residents and staff, as a priority group for mass vaccination with COVID-19 vaccines [4].

Mass vaccination has been identified as the chief strategy to contain the COVID-19 pandemic. The scope of the vaccination effort during the COVID-19 pandemic is unparalleled in modern times. Previous vaccination campaigns, such as for influenza, have typically been conducted over several months and have involved a vaccine that requires only a single dose and can be stored at ordinary refrigeration temperatures. Furthermore, the urgency associated with the need for rapid vaccination has not been experienced since the 1950 s, when polio ran rampant through the US.

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CVS Health has expansive coverage across the US, including approximately 10,000 brick-and-mortar stores across all 50 states, the District of Columbia, and Puerto Rico; 86% of the US population is located within 10 miles of a CVS location. Because of this unique national reach, CVS Health was selected by Operation Warp Speed as a Federal Pharmacy Partner for vaccination of LTCFs [5] and tasked with the vaccination of patients and healthcare workers/staff in 47,907 LTCFs in the US. The vaccines used in this initiative received emergency use authorization in December 2020 (Pfizer on December 21; Moderna on December 28) and LTCF vaccinations were initiated the week of December 21, 2020 [6]. The federal Pharmacy Partnership program ended on April 23, 2021 [6].

In this work, we present a case study on the design, implementation, and deployment of our solution for (a) assigning the optimal CVS locations to LTCFs by minimizing distance between them; and (b) developing a schedule for vaccine administration-distribution to maximize the number of LTCFs covered in the minimum number of days. The efforts of CVS Health and the other Federal Pharmacy Partners in the LTCF vaccination program were instrumental in effectuating a rapid and dramatic reduction in hospitalizations and deaths due to COVID-19 [7,8]. Our learnings and framework can potentially be leveraged by other organizations, healthcare clinics, and countries to address barriers to vaccination and speed up delivery of care.

2. Methods

2.1. Problem formulation

Our objective was to match CVS retail locations that had pharmacies capable of providing the COVID-19 vaccine (referred to hereafter as “CVS depots”) with LTCFs while taking into account multiple challenges (such as distance, residential population, throughput constraints, CDC requirements, as described below), and to develop a schedule to minimize the time for residents/staff in an LTCF to receive both the first and second shots from the mapped location. We selected a subset of the CVS depots to form logistical distribution hubs to reach all LTCFs in our assigned regions, including skilled nursing facilities (SNF) and assisted living facilities (ALF). Depot selection was optimized by a spatio-geographical model to ensure a uniform reach of distribution, taking into account features such as being open for 24 h/7 days per week and access to cold-chain compliant freezers embedded with real-time temperature monitoring because of the extreme temperature sensitivity of the vaccines [9].

Our algorithms for optimizing vaccination at LTCFs solved the LTC vaccine distribution problem in two steps, which are detailed in subsequent sections:

1. Assignment. We proposed an optimal solution to the depot-LTCF assignment problem by modeling our problem as a *minimum-cost flow* problem [10]. This had two advantages: first, it was an established and known problem in network flows, with computationally efficient solvers; second, it was general enough to allow modeling the constraints encountered in our settings.
2. Scheduling. Given the optimal assignments achieved in Step 1, we devised an algorithm to minimize the number of days needed to vaccinate LTCFs in every state and to compute schedules for the clinics to orchestrate the two doses at the recommended dosing interval. The algorithm further optimized scheduling by strategically clustering several small LTCFs together and pairing them with a large LTCF to determine which group of LTCFs could be vaccinated on the same day, given capacity, distance, and supply constraints.

2.2. Data source/availability and statistical programs

Our dataset was derived from the following inputs:

- Details on partner LTCFs by state.
- Details on CVS depot locations by state.
- Distances between depot-LTCF pairs by state, and distance threshold (of 75 miles) by the CDC.
- Capacity constraints provided by the vaccine provider, such as number of immunizers per team and number of people who could be vaccinated per immunizer.
- Jurisdiction-vaccine provider partnerships (Moderna or Pfizer as the vaccine manufacturer).

The data source on details of LTCF locations and occupants by state, provided by the CDC, is considered protected under the Health Insurance Portability and Accountability Act (HIPAA) and thus cannot be published here. The data source on locations of CVS depots is publicly available [11]; general locations of selected depots are shown in [Supplementary Fig. 1](#).

We implemented the algorithms in Python, used network analysis package (networkX version 2.5), and deployed it on Azure Databricks cluster. Further, to improve usability for field managers working on operationalizing the effort involved, we also developed a User Interface tool (written in PySpark and deployed in Databricks cluster) for sending updated daily schedules in real-time for the duration of the program. The tool built on the results of the algorithms, incorporated last-minute changes/cancellations, and sent the resulting schedule to field managers working in CVS retail depots.

2.3. Staffing and mapping constraints

[Table 1](#) shows the throughput based on staffing strategy per hour by LTCF type (SNF or ALF). These staffing numbers were current as of Dec 16, 2020. The throughput numbers were assumed to be the same for both types of mRNA vaccine (Pfizer and Moderna). Logistically, we assumed that immunization occurred for a maximum of 6 h per day in any LTCF, with the remaining 2–3 h assigned to travel and administrative tasks. We calculated throughput for between 1 and 3 immunizers (and a registration/queueing staff if needed), which can be scaled up to K immunizers based on need. The state-vaccine provider partnerships are shown in [Supplementary Fig. 2](#).

For LTCF vaccination distribution, we were required by the CDC to map every LTCF clinic to exactly one depot within 75 miles with a constraint that the depot had to be located in the same state as the LTCF. Our framework can be easily generalized to solve for a national-level distribution strategy should state constraints no longer apply.

2.4. Modeling for the assignment problem (assigning LTCFs to depots)

We modeled the assignment problem represented in [Fig. 1](#) as a bipartite matching problem in graph G and then transformed it into a network flow graph G' . To capture the effort to distribute vaccines to an LTCF, we calculated the number of days it would take for immunizers to complete vaccinating a specific clinic (denoted as $ltc_days(m)$ for clinic m) based on the number of initial doses needed (represented as $doses(m)$ for clinic m) and the number of immunizers needed to administer vaccinations at clinic m (represented as $num_immu(m)$ for administering $doses(m)$ vaccines at clinic m). We obtained $num_immu(m)$ by referring to the data available on hourly vaccine administering capacity provided by Pfizer and Moderna ([Table 1](#)). To compute $ltc_days(m)$ from

Table 1
Vaccine administering capacity and throughput.

Registration/ queuing staff	Immunizers	Immunizations per hour			Immunizations per 6 h		
		SNF	ALF	In-store	SNF	ALF	In-store
0	1	6	7	5	36	42	30
1	1	8	10	6	48	60	36
1	2	16	20	12	96	120	72
1	3	24	30	18	144	180	108

ALF = assisted living facility; SNF = skilled nursing facility.

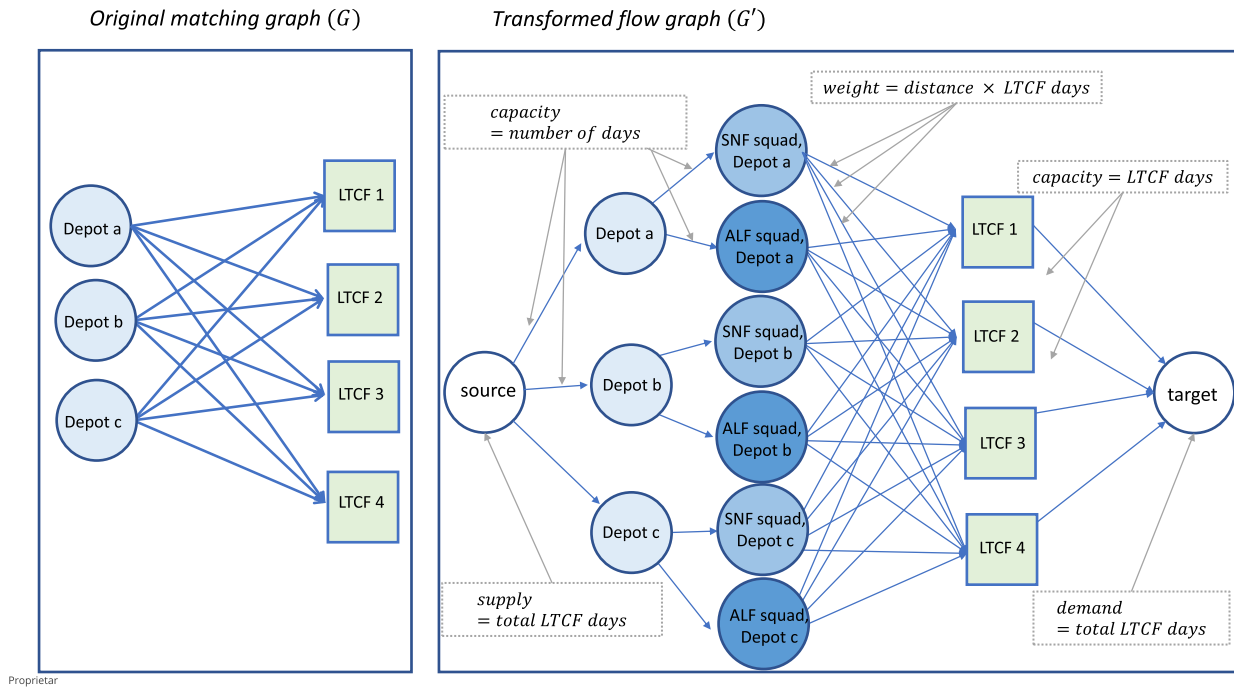


Fig. 1. Original matching graph, G (left), and transformed flow graph, G' (right). For the sake of illustration, three depots (a, b, c) and four LTCFs are shown. For each depot node, one auxiliary node and a pair of nodes indicating SNF and ALF counterparts are added. All edges have weights and/or capacities, and nodes have demand or supply as indicated here. ALF = assisted-living facility; LTC = long-term care facility; SNF = skilled nursing facility.

$num_immu(m)$, given that the maximum number of immunizers we can send to an LTCF is K immunizers per day, we used the following equation:

$$ltc_days(m) = \begin{cases} \left\lceil \frac{num_immu(m)}{K} \right\rceil & \text{if } num_immu(m) \bmod K = 0 \\ \left\lceil \frac{num_immu(m)}{K} \right\rceil + 1 & \text{if } num_immu(m) \bmod K \neq 0 \end{cases}$$

In our case, the maximum number of immunizers that could be sent to any LTCF was $K = 6$; so for $num_immu(m)$ between 0 and 6 immunizers, $ltc_days(m)$ would compute to 1 day, between 6 and 12 immunizers, it would compute to 2 days, and so on. Finally, num_days represented the minimum number of days needed for a state to find a feasible solution for the assignment problem such that all LTCF residents in that state are vaccinated with their first dose.

Our goal was to solve the assignment problem for each state by matching each depot with an LTCF such that:

- The total distance between depot-LTCF pairs was minimized.
- Every LTCF was connected to at most one depot.
- Every depot sent out at most K immunizers on a given day to be distributed across SNF and ALF clinics.

2.4.1. Graph construction

Beginning with graph G on the left in the matching problem shown in Fig. 1, we constructed a flow network graph G' on the right with the aim of assigning LTCs to depots to minimize the total distance driven subject to the constraints described above as follows:

Graph nodes: We first added a source node s with supply equal to $\sum_{m=1}^M ltc_days(m)$ and a target node t with demand equal to $\sum_{m=1}^M ltc_days(m)$. Note that this symbolizes that the aggregate demand by LTCFs is satisfied by the aggregate supply from all the CVS depots. We then added two auxiliary depot nodes for each depot: one for the work it does for vaccinating 'SNF' and another node for work it does for vaccinating 'ALF'. For depot node a , 'SNF' and 'ALF' auxiliary nodes are represented as SNF squad, Depot a , and ALF squad, Depot a , respectively (Fig. 1). These auxiliary nodes were added to take into account workload constraints of each depot and will be explained further in the section describing construction of the graph edges. Finally, we added one node per LTCF, and assigned it a demand of $ltc_days(m)$ for LTCF m . This symbolizes the number of days it takes for the inhabitants of LTCF m to be vaccinated.

Graph edges: We added edges between source node s and depot nodes with capacity equal to num_days and further added an edge connecting a depot to each of its auxiliary 'SNF' and 'ALF' nodes

with capacity also equal to num_days . This, together with the edge capacity num_days from source to each depot, takes into account the constraint that individual or combined workloads from a depot must not exceed the total workload a depot can manage. We then added edges between the SNF squad, Depot a node and the LTCF clinic m with weight equal to $dist(a, m) \times ltc_days(m)$, and between the ALF squad, Depot a node and the LTCF clinic m with weight equal to $dist(a, m) \times ltc_days(m)$, which denotes the total driving distance needed for vaccinating LTCF m from depot a .

2.4.2. Solving the minimum-cost flow problem

We varied num_days during our computation to find the minimum number of days within which the LTCFs could be optimally vaccinated. This accounts for the workload constraint that the depot can do a work equivalent to at most num_days towards administering the first dosage to LTCFs assigned to it (within 21 or 28 days depending on the vaccine).

It is well-known in the literature that supply–demand flow problems as modeled by G' can be solved optimally in a computationally efficient manner [10,12,13]. Moreover, when the edge capacities and weights are integers, as in our case, the flow in the optimal solution on each edge is guaranteed to be an integer. This means that solving the supply–demand flow problem on our graph G' will not only minimize the total distance driven, but the flows on the edges from depots to LTCFs will denote the number of days each LTCF is to be served from the corresponding depot. A minor point to note is that the optimal solution can hypothetically assign a LTCF to be served from two depots (e.g., if a LTCF takes two days to be vaccinated, then it could be served for one day each from two depots). However, such occurrences were extremely rare; almost all LTCFs were fully assigned to one of the depots. If by a rare chance the optimal solution assigned a LTCF to be served from two depots, then we typically modified the solution to assign that LTCF to the depot corresponding to the majority of its workload.

2.5. Scheduling LTCFs assigned to a depot

The vaccination schedule of LTCFs assigned to a depot was computed so that the LTCFs were vaccinated as soon as possible, while respecting the daily workload constraints of a depot. For the purpose of computing LTCFs to be vaccinated on the next available day, we found it more effective to combine a large LTCF with one or two small LTCFs near a depot. This had the benefit of making the workload of a depot fairly distributed across the schedule. To identify the small LTCFs that could be combined with large LTCFs for a day's schedule, we estimated the time taken by a depot to vaccinate a LTCF (denoted by $time_d$) as the sum of three factors: (1) time taken to drive and return; (2) time taken to administer the doses; and (3) extra time (an extra one-half hour was added for Moderna vaccines and an extra hour for Pfizer vaccines). If the total number was less than 4 h, then we considered that clinic 'small.' At most, two such 'small' LTCFs were combined with a large LTCF on a given day, subject to total workload constraints of a depot. We also kept track of the number of individuals remaining to be vaccinated when scheduling large LTCFs that spanned multiple days. If on any day $time_d$ fell below 4 h (due to reduced number of individuals remaining to be vaccinated), then for the last vaccination session it could be treated as a 'small' LTCF and could be combined with another large or small LTCF:

$$time_d(\text{hours}) = \frac{2dist(e)}{20} + \frac{doses(m)}{8} + 1.5 \text{ (if Moderna) or } 1 \text{ (if Pfizer) } + 0.5$$

To devise a scheduling algorithm for administering the first dose, we first considered SNF LTCFs, as these were prioritized over ALF LTCFs according to CDC guidelines. We sorted SNF LTCFs assigned to a depot in the decreasing order of their ltc_days values. If there was a SNF LTCF that was partially served on the previous day, then we prioritized that SNF LTCF on the next available day. Otherwise, we considered the next largest available SNF LTCF yet to be served. We computed the number of immunizers needed to serve the selected SNF LTCF. If it was greater than or equal to K , then we assigned only the single SNF LTCF for that day. We subtracted the number of SNF LTCF inhabitants that were yet to be vaccinated after that day. A positive number indicated that the SNF LTCF was going to be partially served that day and would be prioritized on the next day. If the number of immunizers needed on that day was less than K , then we selected the larger of the two smallest SNF LTCFs at which vaccination would take less than 4 h (see previous paragraph) from the pool of unscheduled SNF LTCFs assigned to the depot.

After scheduling the first dose for SNF LTCFs as described above, we scheduled the first dose to ALF LTCFs using the same algorithm. After we scheduled the first dose for all LTCFs, we again used the above algorithm to schedule the second dose, while taking into account that for any LTCF the second dose must come 21 days after the first dose for the Pfizer vaccine and 28 days after the first dose for the Moderna vaccine.

3. Results

3.1. Distance minimization between matched depot-LTCF pairs

We served 47,907 LTCFs (median number of residents/staff per facility = 70) across the 50 states, Puerto Rico, and the District of Columbia by assigning 1,214 retail stores as depots for vaccine distribution. Our assignment algorithm minimized distances between matched depot-LTCF pairs such that 41% of the LTCFs were within 5 miles of a depot, 74% were within 20 miles, and only 8% mapped to depots farther than 50 miles away (Fig. 2). We verified that LTCFs paired with a depot further than 50 miles away were indeed mapped to the closest depot compared with all available options.

3.2. Load distribution fairness and schedule packing across depots

Fig. 3 shows load distribution on depots by vaccine type across ltc_days , i.e., the number of days required to completely vaccinate all staff and patients in that location given our immunization capacity. Our algorithm efficiently matched depots to LTCFs such that the total load of serving all LTCFs assigned to a depot was fairly distributed across different depots. A majority of depots served a large number of LTCFs with smaller ltc_days (Fig. 3 left), whereas only a few depots served outlier LTCFs with larger values of ltc_days (Fig. 3 right). This fairness in load distribution ensured that all depots could be operationalized in parallel, thus requiring the minimum number of days for delivery of the first shot. All depots finished immunizing LTCFs with the Moderna vaccine by the 28-day mark, which is when the second shots are due for Moderna, and 90% of the depots finished immunizing LTCFs with the Pfizer vaccine by the 21-day mark, the minimum timing for the second dose of that vaccine (Fig. 3).

Across all states, 42% of the LTCFs required only a half day to vaccinate (Fig. 4). Accordingly, strategic clustering of pairs of LTCFs with a given depot helped optimize distribution of the vaccines. By combining several small LTCFs with one large LTCF, the number of depots involved in vaccinating peaked quickly and declined gradually over time, thus allowing us to maximize the ability to deliver

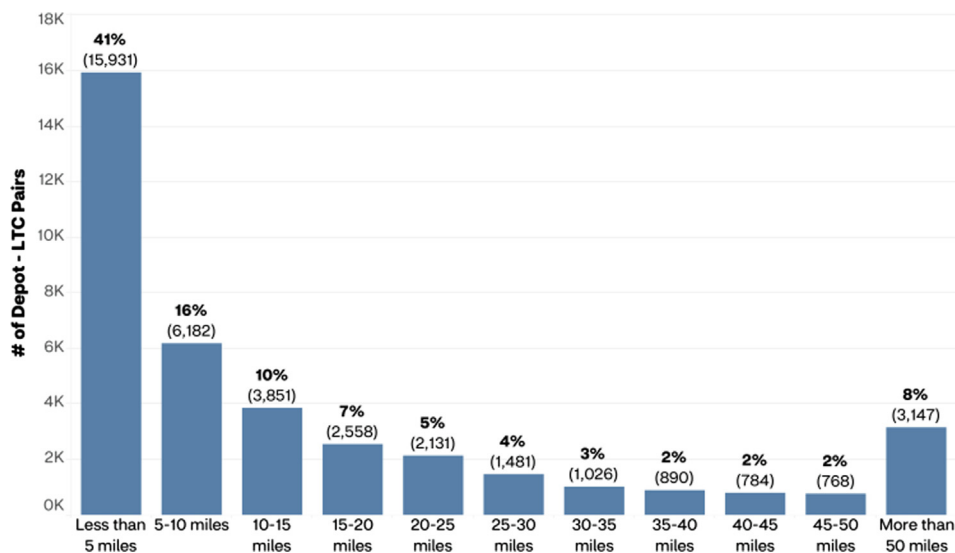


Fig. 2. Optimized distance distribution between mapped CVS depot-LTCF pairs. This optimized distribution was obtained by solving for the minimum-cost flow in the assignment problem.

as many first vaccine doses as possible within the 21/28 day window (Fig. 5).

3.3. LTCF vaccination by state

In 76% of all states, the first vaccination dose was distributed within an average of 9 days after the program started (Fig. 5).

The average distance between depot-LTCF pairs was usually short, and only occasionally exceeded 40 miles in geographic areas where depots and LTCFs were more spread out (i.e., Montana, South Dakota, and Wyoming). California required the longest time (23 days) to vaccinate 706,000 patients with the first dose, which highlights the capacity bottlenecks related to the large number of LTCFs in this populous state.

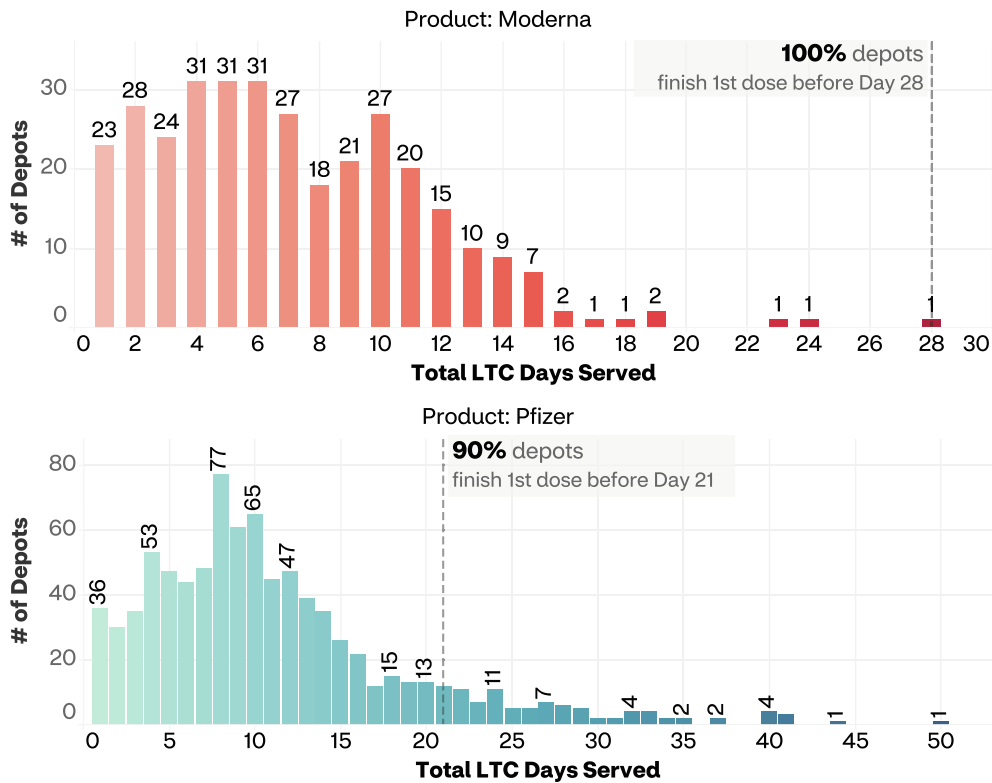


Fig. 3. Distribution of vaccination load across *ltc_days* by vaccine type. Solving for the scheduling problem ensured fair distribution in workload across depots for both vaccine types. As a result, 100% of the depots administering the Moderna vaccine finished with first doses within 28 days (top graphic), and 90% of depots administering the Pfizer vaccine finished within 21 days (bottom graphic).

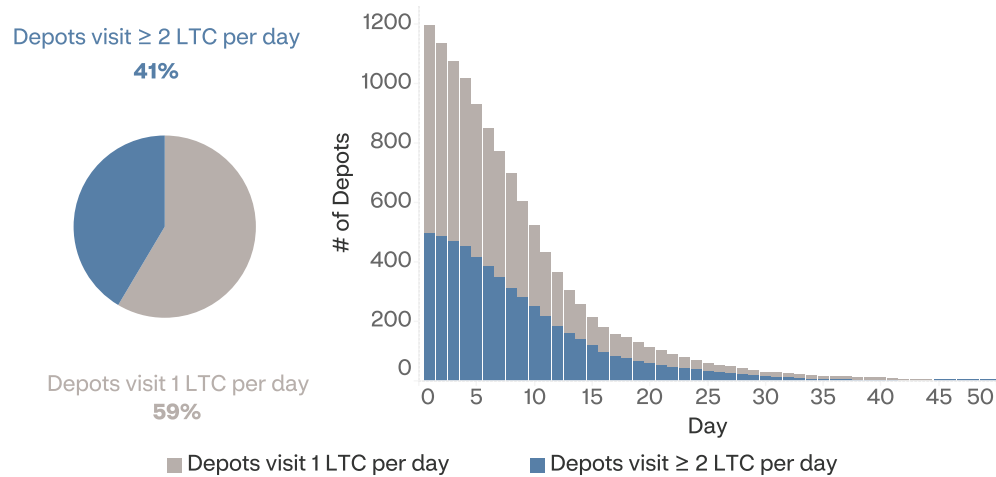


Fig. 4. Single and multiple depot visits per day across all states. Our solution strategically paired LTCFs that could be visited on the same day with a depot for increased vaccination throughput. Forty-one percent of depots visited more than 2 depots per day across all states (left graphic). This strategic pairing resulted in rapid vaccination of LTCFs (right graphic).

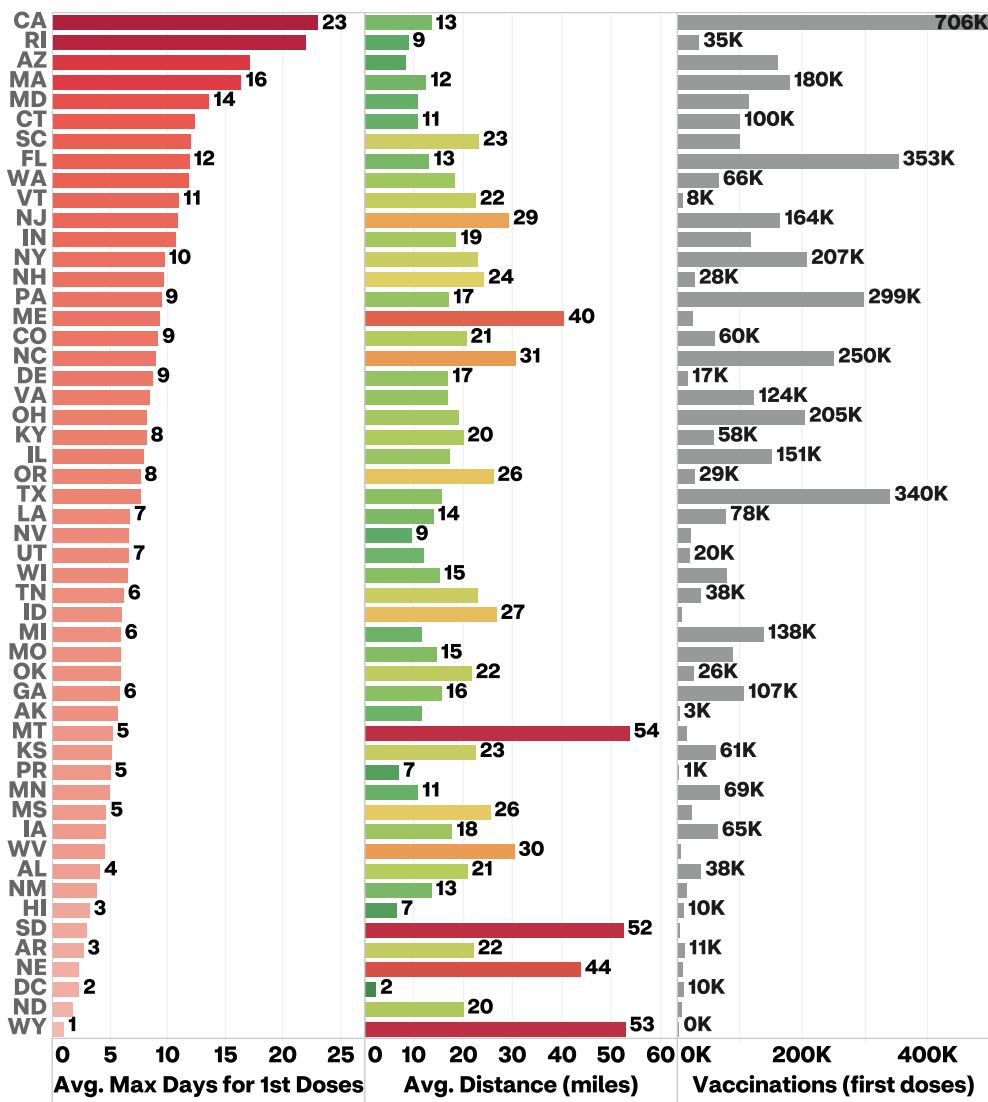


Fig. 5. Key LTCF vaccination metrics by state in the optimized solution. The average of maximum number of days needed for first vaccination dose across depots by state (left graphic); average distance between depot-LTCF pairs in miles (center graphic); and the number of vaccinations (first doses) are shown for each state.

3.4. In-depth assessment of LTCF vaccination in California

An examination of California provides further insights into the challenges faced in that state. California contained more than 15,000 LTCFs serviced by CVS depots (median number of residents/staff per facility = 41). Our strategy of scheduling more than one LTCF per day by combining small LTCFs improved the capacity bottleneck in California. By clustering small LTCFs, we ensured that 57% of depots visited two or more LTCFs in a day (Supplementary Fig. 3). In addition, our scheduling algorithm fairly distributed load by scanning LTCFs based on decreasing order of size and pairing one large LTCF (i.e., an LTCF with more *ltc_days*) with several small LTCFs on each day (Supplementary Fig. 4). We observed that the number of LTCFs covered increased with increasing number of days, and then decreased before tapering off at around Day 18, while the number of assisting depots was maintained across the duration. Most LTCFs had received vaccinations by Day 28; after Day 28, very few depots (< 32) were engaged in immunizing patients/staff.

4. Discussion

Due to the significant burden of COVID-19 on vulnerable individuals living in clusters such as LTCFs, vaccination of LTCF residents and staff was given the highest priority by the CDC [4]. CVS Health was chosen as one of the retail partners for LTCF vaccination. Using the algorithms described here, the first LTCF vaccination dose was distributed within the first 9 days after the start date of the program in 76% of states, and greater than 90% of doses were administered in the minimum amount of time (28 days for the Moderna vaccine and 21 days for the Pfizer vaccine).

The substantial risk of adverse outcomes for LTCF residents who become infected with COVID-19 motivated our work to design algorithms to vaccinate patients in these severely vulnerable communities quickly and efficiently. Ideally, the assignment and scheduling sub-problems associated with an effort such as this would be solved together as a single problem. However, because of several logistical constraints (related to cold-storage, capacity, and time spent in traveling to locations), we took a two-step approach where we obtained an optimal solution for the assignment problem and then proposed an algorithm for the scheduling problem building on top of optimal assignments. While our solution to the assignment problem was already optimal given system constraints, it is possible to design a further optimized scheduling algorithm. However, additional optimization would occur at the cost of higher complexity, including reduced ease of execution and logistical complications. We encountered multiple challenges during this exercise, including the constraint of creating depot-LTCF pairs that were closest within the borders of a given state, rather than closest overall, and the need to evenly distribute load among CVS depots to allow parallel deployment of the vaccination squads. In addition, the vaccine needed to be transported to the target population, rather than having the target population come to a designated location. These unique characteristics added to the logistical difficulties of organizing mobile clinics for vaccine distribution to LTCFs.

Given these challenges, the overall success of efforts by CVS Health and other federal partners to vaccinate residents and staff at LTCFs is remarkable: between the first day of nursing home vaccinations, December 21, 2020, and January 31, 2021, nursing home deaths decreased 66% in the US while deaths in non-nursing home residents (most of whom were not yet vaccinated) increased 61% [7]. Although vaccine efficacy is clearly a critical component of mass vaccination, a recent modeling study found that factors related to implementation and distribution are as or more impor-

tant for the success of vaccination programs than the efficacy of the vaccine itself (within a specified range) [14].

To the best of our knowledge, we are the first to share details on algorithmic implementations for vaccine distribution to clustered communities via mobile clinics applied to a real-life case study deployed on a nationwide scale. Mobile clinics are an efficient means for providing health services to vulnerable communities during high mortality emergencies [15,16]. However, none of the existing work in the literature has addressed the vaccine distribution challenges described here. Previous reports have focused on designing optimal vaccine allocation network from a distribution center to local clinics [17,18], but did not include last-mile vaccine distribution to prioritized patients, the focus of the study reported here. Another line of work revolves around prioritization of populations for vaccine distribution [19–21], whereas in our work the prioritized population (namely, residents in a closely clustered community such as LTCFs) was pre-determined and the challenge was to vaccinate them quickly and efficiently. The last stream of work studies the problem of vaccine distribution under evolving disease propagations modeled via epidemiological models [22,23], which is also very different from our problem. These past works either had idealized assumptions of network models or were simulations based on real data without a deployed application. Reports on vaccine distribution for influenza [24] and COVID-19 [25] come closest in scope to our work in terms of designing optimal vaccine distribution algorithms, but do not provide a solution for the scheduling problem, which we have developed and implemented on a national scale.

Limitations of the study reported here include the inherent trade-off between real-life implementation and comparison with other algorithmic approaches on real-world data. Because the algorithm described here was deployed as part of an actual vaccination distribution program, the results of our case study only reflect outcomes associated with those specific circumstances. We are therefore unable to compare the results of our algorithm with those obtained by other possible algorithms or solutions. On the other hand, more sophisticated algorithms allow comparisons with other algorithmic variations [26,27], but are not deployed in real time and therefore do not provide actual outcome data that can only arise from real-world use.

In conclusion, the vaccine distribution system described here allowed efficient and rapid distribution of vaccines to 47,907 LTCFs from mobile clinics linked to 1,214 CVS depots. This infrastructure may be of use in future LTCF vaccination campaigns. We hope our analysis and insights from the CVS Health LTCF vaccination mobile clinic program will be of value in implementing vaccine distribution strategies across the world, as well as in designing additional healthcare outreach programs that may be well-suited to mobile clinics.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [The authors are employed by and own stock in CVS Health, who funded this work].

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Data availability

Data availability is discussed in Section 2.2. Researchers should contact the corresponding author with any questions or requests.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.vaccine.2021.12.049>.

References

- [1] Coronavirus death toll. Worldometer. <https://www.worldometers.info/coronavirus/coronavirus-death-toll/> (accessed December 1, 2021).
- [2] Curiskis A, Kelly C, Kissane E, Oehler K. What we know-and what we don't know-about the impact of the pandemic on our most vulnerable community. March 31, 2021. <https://covidtracking.com/analysis-updates/what-we-know-about-the-impact-of-the-pandemic-on-our-most-vulnerable-community> (accessed December 1, 2021).
- [3] Harris-Kojetin L, Sengupta M, Lendon JP, et al. Long-term care providers and services users in the United States, 2015–2016. National Center for Health Statistics. February 2019. https://www.cdc.gov/nchs/data/series/sr_03/sr03_43-508.pdf (accessed December 1, 2021).
- [4] Dooling K, Marin M, Wallace M, McClung N, Chamberland M, Lee GM, et al. The Advisory Committee on Immunization Practices' updated interim recommendation for allocation of COVID-19 vaccine—United States, December 2020. *MMWR Morb Mortal Wkly Rep* 2021;69(5152):1657–60.
- [5] Trump administration partners with CVS and Walgreens to provide COVID-19 vaccine to protect vulnerable Americans in long-term care facilities nationwide. U.S. Department of Defense web site. October 16, 2020. <https://www.defense.gov/News/Releases/Release/Article/2384541/trump-administration-partners-with-cvs-and-walgreens-to-provide-covid-19-vaccine/> (accessed December 1, 2021).
- [6] Reporting COVID-19 vaccination data for long-term care facilities. Centers for Disease Control and Prevention web site. April 24, 2021. <https://www.cdc.gov/coronavirus/2019-ncov/vaccines/distributing/long-term-care-facility-vaccination-data.html> (Accessed December 9, 2021).
- [7] Chidambaram P, Garfield R, Neuman T, Levitt L. Is the end of the long-term care crisis within sight? New COVID-19 cases and deaths in long-term care facilities are dropping. Kaiser Family Foundation web site. February 24, 2021 <https://www.kff.org/policy-watch/is-the-end-of-the-long-term-care-crisis-within-sight-new-covid-19-cases-and-deaths-in-long-term-care-facilities-are-dropping/> (accessed December 1, 2021).
- [8] Conlen M, Mervosh S, Ivory D. Nursing homes, once hotspots, far outpace U.S. in Covid declines. The New York Times. Feb. 25, 2021. <https://www.nytimes.com/interactive/2021/02/25/us/nursing-home-covid-vaccine.html> (accessed December 1, 2021).
- [9] Simmons-Duffin S. Why does Pfizer's COVID-19 vaccine need to be kept colder than Antarctica? National Public Radio. November 17, 2020. <https://www.npr.org/sections/health-shots/2020/11/17/935563377/why-does-pfizers-covid-19-vaccine-need-to-be-kept-colder-than-antarctica> (accessed December 1, 2021).
- [10] Kleinberg J, Tardos E. *Algorithm design*. Boston: Pearson/Addison-Wesley; 2006.
- [11] CVS pharmacy. Store locator. <https://www.cvs.com/store-locator/cvs-pharmacy-locations> (accessed December 1, 2021).
- [12] Tomescu AI, Kuosmanen A, Rizzi R, Mäkinen V. A novel min-cost flow method for estimating transcript expression with RNA-Seq. *BMC Bioinf* 2013;14(Suppl 5):S15. <https://doi.org/10.1186/1471-2105-14-s5-s15>.
- [13] Hovav S, Tsadikovich D. A network flow model for inventory management and distribution of influenza vaccines through a healthcare supply chain. *Oper Res Health Care* 2015;5:49–62. <https://doi.org/10.1016/j.orhc.2015.05.003>.
- [14] Paltiel AD, Schwartz JL, Zheng A, Walensky RP. Clinical outcomes of a COVID-19 vaccine: implementation over efficacy. *Health Aff (Millwood)* 2021;40(1):42–52. <https://doi.org/10.1377/hlthaff.2020.02054>.
- [15] McGowan CR, Baxter L, Deola C, Gayford M, Marston C, Cummings R, et al. Mobile clinics in humanitarian emergencies: a systematic review. *Confl Health* 2020;14(1). <https://doi.org/10.1186/s13031-020-0251-8>.
- [16] Pitt C, Roberts B, Checchi F. Treating childhood pneumonia in hard-to-reach areas: a model-based comparison of mobile clinics and community-based care. *BMC Health Serv Res* 2012;12:9. <https://link.springer.com/article/10.1186/1472-6963-12-9>.
- [17] Lim J, Norman BA, Rajgopal J. Redesign of vaccine distribution networks. *Int Trans Oper Res* 2022;29(1):200–25. <https://doi.org/10.1111/itor.12758>.
- [18] Yang Y, Rajgopal J. An iterative cyclic algorithm for designing vaccine distribution networks in low and middle-income countries. International Joint Conference on Industrial Engineering and Operations Management. July 15–17 2019, Novi Sad, Serbia. <https://arxiv.org/ftp/arxiv/papers/1907/1907.10777.pdf> (accessed December 1, 2021).
- [19] Buccieri K, Gaetz S. Ethical vaccine distribution planning for pandemic influenza: prioritizing homeless and hard-to-reach populations. *Public Health Ethics* 2013;6(2):185–96. <https://doi.org/10.1093/phe/pht005>.
- [20] Araz OM, Galvani A, Meyers LA. Geographic prioritization of distributing pandemic influenza vaccines. *Health Care Manag Sci* 2012;15(3):175–87. <https://doi.org/10.1007/s10729-012-9199-6>.
- [21] Tuite AR, Fisman DN, Kwong JC, Greer AL, Chêne G. Optimal pandemic influenza vaccine allocation strategies for the Canadian population. *PLoS ONE* 2010;5(5):e10520. <https://doi.org/10.1371/journal.pone.0010520>.
- [22] Grauer J, Löwen H, Liebchen B. Strategic spatiotemporal vaccine distribution increases the survival rate in an infectious disease like Covid-19. *Sci Rep* 2020;10(1):21594. <https://doi.org/10.1038/s41598-020-78447-3>.
- [23] MacIntyre CR, Costantino V, Trent M. Modelling of COVID-19 vaccination strategies and herd immunity, in scenarios of limited and full vaccine supply in NSW, Australia. *Vaccine* 2021. <https://doi.org/10.1016/j.vaccine.2021.04.042>.
- [24] Rastegar M, Tavana M, Meraj A, Mina H. An inventory-location optimization model for equitable influenza vaccine distribution in developing countries during the COVID-19 pandemic. *Vaccine* 2021;39(3):495–504. <https://doi.org/10.1016/j.vaccine.2020.12.022>.
- [25] Tavana M, Govindan K, Nasr AK, et al. A mathematical programming approach for equitable COVID-19 vaccine distribution in developing countries. *Ann Oper Res* 2021 Jun 3 [online ahead of print] <https://doi.org/10.1007/s10479-021-04130-z>.
- [26] Venkataraman N, Poon BH, Sia C. Innovative use of health informatics to augment contact tracing during the COVID-19 pandemic in an acute hospital. *J Am Med Inform Assoc* 2020;27(12):1964–7. <https://doi.org/10.1093/iamia/ocaa184>.
- [27] Bednarski BP, Singh AD, Jones WM. On collaborative reinforcement learning to optimize the redistribution of critical medical supplies throughout the COVID-19 pandemic. *J Am Med Inform Assoc* 2021;28(4):874–8. <https://doi.org/10.1093/iamia/ocaa324>.